Differential Abundance methods- Simulation Results

Saritha Kodikara

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1 Simulation Results- Scenario 1

In this file, we present results for Taxa 1 simulated under moderate parameter values (i.e. dispersion=0.1 and AR=0.04) from Zero-inflated Beta Regression Model, Negative Binomial Mixed Model, splinectomeR, Zero-inflated Gaussian mixed model and Fast zero-inflated negative binomial mixed model.

```
meta_df<-readRDS("Data/df_meta.Rdata")
list_sc1_ra<-readRDS("Data/RA_Scenario1.Rdata")
list_sc1_co<-readRDS("Data/count_Scenario1.Rdata")
dfcount<- cbind(meta_df,list_sc1_co[[1]])
dfRA<- cbind(meta_df,list_sc1_ra[[1]])
```

1.1 Zero-inflated Gaussian mixed model

```
#Scenario 1 (Relative Abundance)
fit_zigmm<-lme.zig(Taxa_1~Time+Group+Time*Group, random = ~ 1 | Indiv, data = dfRA)
summary(fit_zigmm)

#Scenario 1 (Relative Abundance)-with AR
fit_zigmmAR<-lme.zig(Taxa_1~Time+Group+Time*Group, random = ~ 1 | Indiv,
                     data = dfRA, correlation = corAR1())
summary(fit_zigmmAR)

#Scenario 1 (Counts)
fit_zigmm_count<-lme.zig(Taxa_1~Time+Group+Time*Group+ offset(log(Library_size)),
```

```
                    random = ~ 1 | Indiv, data = dfcount)
summary(fit_zigmm_count)

#Scenario 1 (Counts)-with AR
fit_zigmmAR_count<-lme.zig(Taxa_1~Time+Group+Time*Group+ offset(log(Library_size)),
                    random = ~ 1 | Indiv, data = dfcount, correlation = corAR1())
summary(fit_zigmmAR_count)
```

1.2 Zero-inflated Beta Regression Model

```
#Scenario 1
df_cov = data.frame(Time = meta_df$Time, Group=meta_df$Group,
                      Time_Group=meta_df$Time*meta_df$Group)
fit_zibr<-zibr(logistic.cov = data.frame(Time = meta_df$Time, Group=meta_df$Group,
                      Time_Group=meta_df$Time*meta_df$Group),
                     beta.cov = df_cov,
                     Y =list_sc1_ra[[1]]$Taxa_1, subject.ind = meta_df$Indiv,
                     time.ind =  meta_df$Time)
fit_zibr
```

1.3 Negative Binomial Mixed Model

```
#Scenario 1
fit_nbmm<-glmm.nb(Taxa_1~Time+Group+Time*Group+ offset(log(Library_size)),
                    random = ~ 1 | Indiv, data = dfcount)
summary(fit_nbmm)

#Scenario 1-AR
fit_nbmmAR<-glmm.nb(Taxa_1~Time+Group+Time*Group+ offset(log(Library_size)),
                    random = ~ 1 | Indiv, data = dfcount, correlation = corAR1())
summary(fit_nbmmAR)
```

1.4 Fast zero-inflated negative binomial mixed model

```
#Scenario 1
fit_zinb<-glmm.zinb(Taxa_1~Time+Group+Time*Group+ offset(log(Library_size)),
                    random = ~ 1 | Indiv, data = dfcount)
summary(fit_zinb)

#Scenario 1-AR
fit_zinbAR<-glmm.zinb(Taxa_1~Time+Group+Time*Group+ offset(log(Library_size)),
                    random = ~ 1 | Indiv, data = dfcount, correlation = corAR1())
summary(fit_zinbAR)
```

1.5 SplinectomeR

```r
#Scenario 1
# Test for difference in RA change over time between groups 0 and 1
fit_permuspliner <- permuspliner(data =  dfRA, x = 'Time', y = 'Taxa_1',
                       cases = 'Indiv', category = 'Group', groups = c('0','1'))
fit_permuspliner$pval

# Test for non-zero trend in RA over Time
fit_trendyspliner <- trendyspliner(data = dfRA, x = 'Time', y = 'Taxa_1',
                        cases = 'Indiv', perms = 999)
fit_trendyspliner$pval
```